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Morphological Properties for Feature Extraction of Geometrical shapes

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Abstract:* Geometric shapes are very important in the field of pattern recognition and have played a large role in the field of computer vision and have adopted many algorithms in this field. The present study focuses on important features that have been elicited form various shapes, such as(rectangles, squares, triangles, polygon, circle, ellipse, irregular) only after counting the co-occurrence matrix of these shapes since it has certain important features. When studying the features of the co-occurrence matrix the power of certain features and the weakness of others appear. In the shapes, the features of homogeneity, energy, and contrast were of high affectivity especially when eliciting the characteristic of the geometrical shapes that have been counted after certain primary processing and operating of cutting and reshaping the structure needed for the shape. When applying the algorithm depended on in the present study on the geometrical shapes of different dimension, the results have shown the ability of recognition and distinction reaching 60% apply on 35 sample when considering between the three features. The algorithm was programmed using MATLAB R2010a for Windows 7 operating system on the computer that has the following specifications: (Processor Intel (R) Core (TM) i5, CPU 640 M & 2.53 GHZ, RAM 6GB).

Keywords: **Co-occurrence matrix, Feature Extraction, , shapes, skeleton, Thinning.**

I. INTRODUCTION

Detection of geometric features in digital images is an important exercise in image analysis and computer vision [1]. Many properties of objects in our world are strongly determined by geometric properties, the applications of shape analysis extend over almost every applied scientific and technological area, from the smallest to the largest spatial scales. For instance, the strength of composites is directly related to the shape of its constituent crystal grains, the shape of biological entities provide an immensely important clue about the interactions between themselves and with the environment. The relationship is no less dramatic at larger scales, where the properties of a wing design or a mechanical piece are almost completely defined by their respective geometry. Indeed, when properly and carefully applied shape analysis provide an exceedingly rich potential for applications in the most diverse areas, from material sciences to biology and neuroscience [2].

The Hough Transform (HT) is a standard method for shape recognition in digital images [3,4]. It was initially used to recognition straight lines [5, 6] and later extended to circle [7], ellipses [8] and arbitrarily shaped objects [9]. Its advantages include robustness to noise, robustness to shape distortions and to occlusions/missing parts of an object. Its main disadvantage is the fact that computational and storage requirements of the algorithm increase as a power of the dimensionality of the curve. This means that for in a straight line the computational difficulty and storage space supplies are O(n2), for circles O(n3) and for ellipses O(n5[10].

This paper proposes approach to detection new features for a group of regular geometrical shapes of pictures, and to classify this group into categories depending on four features including energy, contrast, correlation and homogeneity all of which can be obtained from a co-occurrence matrix.

II. RESEARCH OBJECTTIVE

The main objective of the research is to look for an algorithm to extract features of geometrical shapes in digital images based on evaluating some morphological properties.

III. METHODOLOGY

A. Thinning

Thining is a morphological process that is used to delete forground pixels from binary images, somewhat like erosion or opening. It is used for several applications, especially for the skeletonization. The main advantages of thinning image processing as a basic step and recognition pattern is to limit the amount of data from the input binary image, which will make it easier to extract the basic attributes of the object [11].

Thinning is normally only applied to binary images, and produces another binary image as output [12], see figure (1).

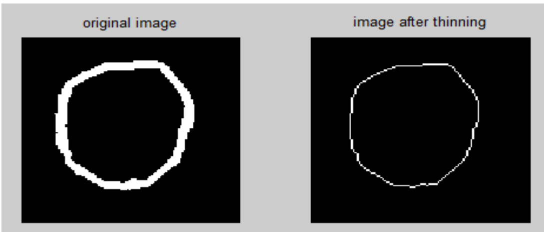

Fig (1) Thinning operation

On a daily basis, the thinning process is calculated by translating the parent element of the structure to each pixel position as possible in the image, and in each position it compares it with the basic image pixels. The thinning of a set A by a structuring element B is shown in Equation (1) [13].

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$$A \otimes B = A - (A \otimes B)$$
$$= A \cap (A \otimes B)^{c} \qquad (1)$$

There's a more useful expression of thinning based on the sequence of elements of the structure set out in the equation (2)[13].

$$\{B\} = \{B^{1}, B^{2}, B^{3}, \ldots, B^{n}\} \qquad (2)$$

Where B^{i} is rotated version of B^{i-1}. It can be shown in Equation (3) [13].

$$A\square\ \square\ \{B\} = ((\ldots((A\square\ \square\ B^{1})\square\ \square\ B^{2})\ldots)\ \square\ B^{n}) \qquad (3)$$

The structuring elements used in (1) are shown in figure2 [13].

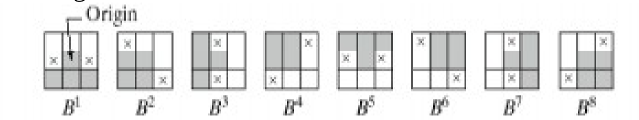

Fig (2) Sequence of rotated structuring elements used for thinning.

B. Skeletonization

Skeletonization is a conversion of a component of a digital image into a subset of the original component. There are different classes of skeletonization methods one class is based on the distance conversion, and a specific subset of the converted image is a instance skeleton. The skeleton of the region is defined by the Medial Axis Transform (MAT) proposed by Blum. The MAT of a region R with edge b is defined as follows: Find the nearest neighbour for each point p of R, if p has more than one neighbour then p belongs to medial axis (skeleton) of R. The concept selection of a distance measure [14]. Figure (3) shows examples that use Euclidean distance as measure.

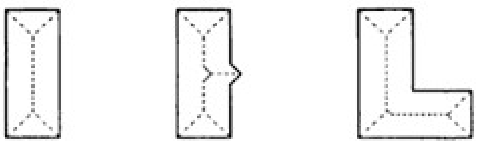

Fig (3) The medial axis represents some minor geometric shapes.

Skeletionization is an important technique used in many fields in digital image processing. Its goal is to reduce an object R within an image in order to generate an object S (generally called as skeleton) whose thickness is just one pixel and it is generally connected, preferable on a specific metric. The objects geometric characteristics are proposed and those properties helps to conserve the "geometric form" of the object in the final skeleton [15]. The morphological skeleton can be obtained from the equation (4) [13].

Where $\square_{k=0}^{k}$:for hole region

$$S(A) = \square_{k=0}^{k} S_{k}(A) \qquad (\cdot$$

Where S k (A) can be given by Equation (5)[14] .

$$S_{k}(A) = (A \ominus KB) - (A - KB) \circ B\ .\ .\ .\ .\ \ominus A) \qquad (5)$$

K successive erosions are carried out and k is the last iterative step before A erodes to an empty set. Group A can be recreated using equation (6) [14].

$$A = \square_{k=0}^{k} (S_{k}(A) \oplus KB) \qquad (6)$$

Where k successive dilations are carried out in the same manner. It is given by Equation (7) [13,14].

$$(S_{k}(A) \oplus KB) = ((\ldots(S_{k}(A) \oplus B)\ B\ \oplus \ldots) \qquad (7)$$

IV. SHAPE REPRESENTATION

Shape is a very important visual and semantic feature used to describe image, and it can be revealed by image pixels' regional distribution. To binary image [16]. Shape representation can be categorized into two kinds: Contour-based methods and region-based methods. Contour-based approaches are more common in applications because they're accordant to the human sight habits and need less information to store [17].

Based on whether the shape is represented as a whole or represented by segments, shape representation can be classified into two other categories as follows: global approaches and structural approaches. The global approaches use a feature vector derived from the integral boundary to describe the shape in contour-based approaches.

Common global features are: area, circularity, eccentricity, major axis orientation, bending energy, convexity, ratio of principle axis, circular variance and elliptic variance. There are several main properties of an object, such as shape, color, texture, brightness, etc. Accordingly, the objects are classified in different ways. In general, the shape information is mainly used to characterize objects [17].

A. Shape Description

To describe the outer shape via some statistical expression:

1. Geometric descriptions

- Area - Total number of points in the region.
- Length.
- Perimeter.
- Elongation (eccentricity) - The ratio of the maximum length of line or chord that spans the region to the minimum length chord.
- Principle axes of inertia.
- Compactness - The ratio of the square of the perimeter to the area of the region.
- Moments of inertia.

The description of these terminology involve the definition of moment, we will discuss them as we talk about moment [18].

2. Topological descriptions

- Connectivity - The number of neighboring features adjoining the region.

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- Euler number - The number of regions minus the number of holes [18].

V. FEATURE EXTRACTION

The extraction feature plays a very important role to fill the gap between what we can get (features can be extracted by a computer) and what we want to have (image understanding) [18].

In computer vision society, a feature is defined as a function of one or more measurements, the values of some quantifiable property of an object, computed so that it quantifies some significant characteristics of the object. One of the biggest advantages of extracting feature lies that it significantly reduces the information (compared with the original image) to represent in the image to understand the image content [18].

There has been tremendous work on different approaches to the detection of various kinds of features in images. These features can be classified as follows:

- General features: Features in this category are all application independent, e.g. color, texture, and shape. According to abstraction level, they can be further divided into:
  Pixel-level features: Can be calculated at each pixel, e.g. color, location, and the first and second derivatives of gray-scale values at each pixel.
- Local features: Can be calculated over the results of image segmentation and edge detection algorithms, that is, they are all based on a part of an image with some special properties. Object shape is an example of such feature.
- Global features: Should be calculated over the entire image or just regular sub-area of an image. Usually, they are in fact the statistical properties of an image, e.g. histogram, mean, variance, and moment.
- Domain-specific features: Features in this category are all application dependent, e.g. human faces, fingerprints, and conceptual features, which are synthesis of low-level features for a specific domain aim.

In general all features can be coarsely classified into low-level features and high-level features. Low-level features can be extracted from native images, where extracting a high-level feature should be based on low-level features [18].

In this research a new idea for detection the features for a group of geometrical shapes was introduced by achieving the features seen well, of the co-occurrence matrix (i.e. depending on energy, contrast, correlation, homogeneity).

VI. CO-OCCURRENCE MATRICES

The Co-occurrence matrix is used primarily to describe the texture of the region, but it can also be used in image maps to measure the number of times a two pixel parameter is given [19]. We can know r the spatial relationship Left, above, etc., Cr co-occurrence matrix for this relationship r calculates the number of times the pixel where i is valued with the pixel j by relationship r.

The structure characteristics of the gray levels assume that the structure information in the picture contains 18 spatial relationships between the pixels in the image. This is the first parameter of the gray level Co-occurrence matrix. This is a guess or estimate of the potential density function of the second rank of the points in picture, and the characteristics are obtained as statistics from a matrix The GLCM matrix, which is defined by equation (1), has GLCM inputs (n, m) equal to the number of points appearing at grayscale n, m respectively with the separation of (dr, dc) of points figure (1). The number of points on this estimate obtained is given by equation (2). If Co-occurrence matrix normalized taking into account R, then input represents the possibility of the presence of pairs of pixel levels of gray n, m with separation (dr, dc). We will choose dc = 0 and dr change between 1 to 10 in column wise [20] [21].

$$glcm(n,m) = \sum_{(i,j),(i+dr,j+dc)\epsilon ROI} 1_{\{Img(i,j)=n,Img(i+dr,j+dc)=m\}} \quad (8)$$

$$R_{glcm} = \sum_{(i,j),(i+dr,j+dc)\epsilon ROI} 1 \quad (9)$$

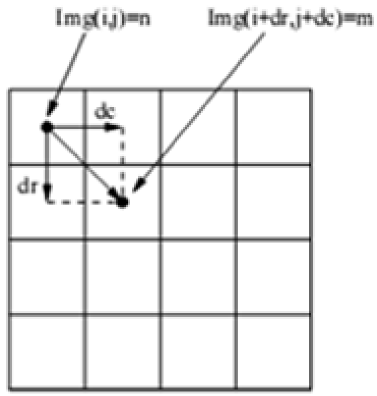

Fig (4) Generation of GLCM (n,m).

A. Creating a Gray-Level Co-occurrence Matrix

To configure GLCM, the co-occurrence matrix for gray levels often calculates the intensity of the pixel (gray level) of n in a spatial relation to a pixel of m, primarily the spatial relationship defined as a pixel of interest and its adjacent pixel horizontally on the right directly, The element (n, m) produced in the co-occurrence matrix is simply the sum of the number of pixels that have a value of n in the spatial relationship specified for the pixel of m in the input image.Because processing requires a calculation of the co-occurrence matrix for the full variable range in the image, this is not desirable, so using the measures to reduce the number of density values in gray images from 256 to 8, the number of gray levels determines the size of the co-occurrence matrix[21].

The grayscale co-occurrence matrix can reveal some properties about the spatial distribution of gray levels in

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the image structure. For example, if most of the entries in the co-occurrence matrix are centered along the diameter, the coarse structure takes into account the specified distance [21]. Figure (5) show a clear basic example to generate GLCM matrix.

I

1	1	5	6	8
2	3	5	7	1
4	5	7	1	2
8	5	1	2	5

GLCM

	1	2	3	4	5	6	7	8
1	1	2	0	0	1	0	0	0
2	0	0	1	0	1	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0
5	1	0	0	0	0	1	2	0
6	0	0	0	0	0	0	0	1
7	2	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	0

Fig (5) Process Used to Create the GLCM

B. Description of Two-dimensional Co-occurrence Matrices

The two-dimensional co-occurrence matrix proposed by Haralik in 1970 is typically used in texture analysis because it is able to take spatial dependence of grayscale values in the image [22]. A 2D co-occurrence matrix P is a matrix of dimensions (n, n), where n is the number of gray levels in the image. For computational efficiency the number of gray levels can be reduced and thus the size of the co-occurrence matrix is reduced. The matrix is represented as an accumulator, so P (i, j) calculates the number of point pairs that have the intensity i and j. Points pairs It can be represented by a shift vector d=(dx, dy), where dx represents the number of points that travel along the x-axis and dy axis of the number of points that travel along the y-axis in the image slice[15].

In order to determine this spatial dependence of grayscale values, different properties of the structure must be calculated as suggested by Haralick [15,16], including Entropy, Contrast, Maximum Probability, Variance, Energy (Angular Second Moment), Sum Mean (Mean), Homogeneity, Correlation, Inverse Difference Moment, and Cluster Tendency. For the formulas and descriptions of these characteristics are found in Table (1) [16].

Table (1) The co-occurrence features

Feature	Formula	What is measured?
Entropy	$-\sum_{i}^{M}\sum_{j}^{N} P[i,j]\log P[i,j]$	Measures the randomness of a gray-level distribution. The Entropy is expected to be high if the gray levels are distributed randomly through out the image.
Energy(Angular Second Moment)	$\sum_{i}^{M}\sum_{j}^{N} P^2[i.j]$	Measures the number of repeated pairs. The Energy is expected to be high if the occurrence of repeated pixel pairs is high.
Contrast	$\sum_{i}^{M}\sum_{j}^{N} (i-j)^2 P[i.j]$	Measures the local contrast of an image. The Contrast is expected to be low if the gray levels of each pixel pair are similar.
Homogeneity	$\sum_{i}^{M}\sum_{j}^{N} \frac{P[i.j]}{1+\|i-j\|}$	Measures the local homogeneity of a pixel pair. The Homogeneity is expected to be large if the gray levels of each pixel pair are similar
SumMean (Mean)	$\frac{1}{2}\sum_{i}^{M}\sum_{j}^{N} (iP[i,j]+jP[i,j])$	Provides the mean of the gray levels in the image. The SumMean is expected to be large if the sum of the gray levels of the image is high.
Variance	$\frac{1}{2}\sum_{i}^{M}\sum_{j}^{N} ((i-\mu)^2 P[i,j]+(j-\mu)^2 P[i,j])$	Variance tells us how spread out the distribution of gray-levels is. The Variance is expected to be large if the gray levels of the image are spread out greatly.
Correlation	$\sum_{i}^{M}\sum_{j}^{N} \frac{(i-\mu)(j-\mu)P[i.j]}{\sigma^2}$	Provides a correlation between the two pixels in the pixel pair. The Correlation is expected to be high if the gray-levels of the pixel pairs are highly correlated.
Maximum Probability (MP)	$\underset{i,j}{\overset{M,N}{Max}} P[i,j]$	Results in the pixel pair that is most predominant in the image. The MP is expected to be high if the occurrence of the most predominant pixel pair is high.
Inverse Difference Moment (IDM)	$\sum_{i}^{M}\sum_{j}^{N} \frac{P[i.j]}{\|i-j\|^k} \quad i \neq j$	Inverse Difference Moment tells us about the smoothness of the image, like homogeneity. The IDM is expected to be high if the gray levels of the pixel pairs are similar.
Cluster Tendency	$\sum_{i}^{M}\sum_{j}^{N} (i+j-2\mu)^k P[i,j]$	Measures the grouping of pixels that have similar gray-level values.

VII. PROPOSED ALGORITHM

The proposed algorithm will be achieved to look for the properties of the various geometrical shapes (circle, ellipse, rectangle, polygon, triangle, irregular) and different dimensions vary from (50,50) to (300,300) for each, then try to recognize the shapes depending on the four features produced by out come from the co-occurrence matrix by applying the following steps:

- The process of acquiring a digital image of geometric shape.
- Initialize input image (binary image color and dimensions ranging between (50,50) to (300 ,300)) for each shape listed)
- Continuous process of thinning to obtain the Skelton image that thickness one pixel.
- Calculate the co-occurrence matrix for the Skelton image.
- Find the four features (homogeneity, energy, contrast, correlation) from the co-occurrence matrix.
- Find the most efficient mathematical model to represent the relationship between the change in the dimensions of the image and each one of the four features and the various geometrical shapes
- Calculate the value of the coefficient of determination, standard error and the significant level of each mathematical model
- Search for the coverings features

VIII. RESULT DISCUSSION

After the application of the proposed algorithm on geometric shapes and with different dimensions showing the extent to which each of the four features affected by the change of dimensions of the image of the geometric shape. By studying of the relationship between the dimensions of the image is estimated in pixels with homogeneity feature and after testing a set of polynomial equations found that the logarithmic model was the most efficient (Y = 0.0162ln (x) +0.9039)), where the coefficient of determination (R2 = 0.94) and a standard error of (Std_Err = 0.002) and the significant level (Sig = 0.003), indicating the efficiency of the graphic representation of this relationship, ie that 94% of the changes in the feature of homogeneity due to the change in dimensions of the image and 6% attributed to other factors not measured. As a result of the high coefficient of determination and the reduction of the standard error value, the logarithmic equation is considered efficient in the graphic representation of the independent factor (image dimensions) in the values of the dependent factor (image homogeneity feature) as shown in figure (6).

As shown in Figure (7) to study the effect of the change in the dimensions of the image is estimated in pixels in contrast feature and when applying a set of polynomial equations found that the most powerful model is the power model (y = 2.986.X-0.952) where the

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relationship is reversed, Increasing the dimensions of the image results in a lack of contrast in the image.

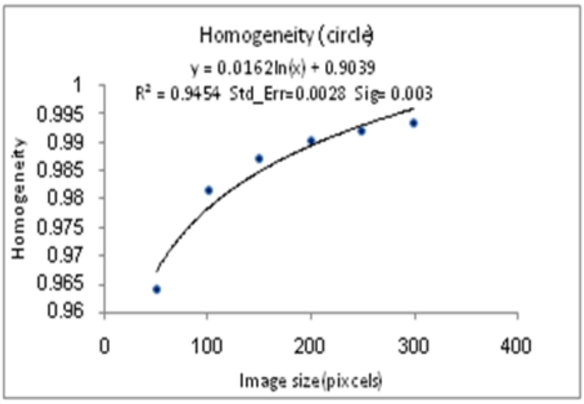

Fig (6) The effect of image dimensions is estimated by pixel in the values of the homogeneity feature of the image geometric shape.

The coefficient of determination (R2 = 0.99) and the standard error (Std_Err = 0.002) and the significant level (Sig = 0.003), indicating the efficiency of the representation of the graph. Where 99% of the changes that occur The value of the variance is due to the change in the dimensions of the image and 1% due to other factors not measured as shown in figure (2).

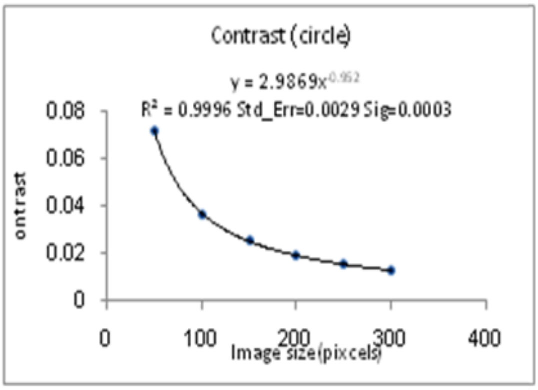

Fig (7) The effect of image dimensions is estimated by pixels in the contrast feature values of the image geometric shape.

As for the relationship of the energy feature with the dimensions of the image and after the adoption of a set of equations was found that the logarithmic model is the best model in the representation of this relationship (y = 0.0707ln (x) +0.5769), where the coefficient of determination (R2 = 0.95) and the standard error (Std_Err = 0.003) and with the significance level (sig = 0.01), ie, the ratio of the effect of changing the dimensions of the image to the energy values of 95% and 5% of the remaining changes is due to other factors that are not measured. It is highly efficient in the graphic representation of the effect of the independent factor to dimension the image in the energy values of the image between the values calculated using the relationship and the real values of the energy feature and Figure (8) shows the degree of compatibility.

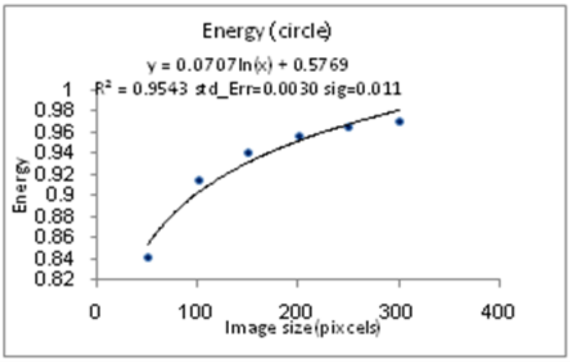

Fig (8) The effect of image dimensions is determined by pixels in the energy values of the image geometric shape

When you study the relationship of the correlation feature to the change in the dimensions of the image and after the application of several equations, the logarithmic model was found to be more efficient to represent this relationship (y= 0.0229ln (x) +0.1361). The coefficient of determination (R2 =0.67) and standard error (Std_Err = 0.002) with a significant level of (sig = 0.01). The percentage of the effect of the image dimensions in the correlation values of the image was 0.67% and 33% . As a result of the low coefficient of determination, this feature is weak affected to change the dimensions of the image as shown in Figure (9).

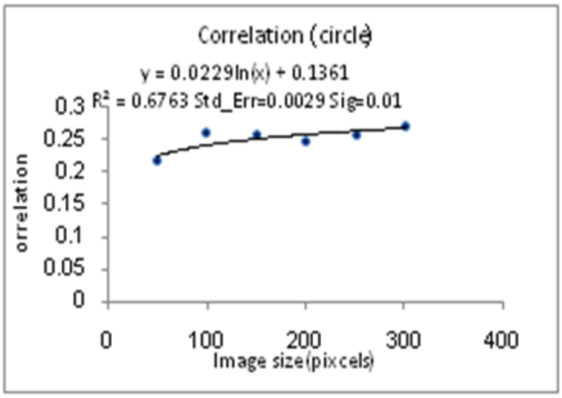

Fig (9) The effect of image dimensions is determined by pixels in the correlation feature values of the image geometric shape.

In the above discussion, we conclude that energy and homogeneity features are affected by large changes in image dimensions. The contrast feature is inversely affected. The correlation feature, however, is weak as the dimensions of the image change. The three features of homogeneity, energy, and contrast give a topical distinction to the shape, but the correlation property is weak in the distinction of form.

The results in Table (2) and Table (3) in Appendix A, respectively, show the values of the four features of the geometric shapes, the measured values of the coefficient of determination, standard err and significant level of the four properties, are drawn in the appendix B.

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IX. RECOMMENDATIONS AND FUTURE WORK

- Connect-based algorithm to distinguish the shapes in the classification of maps drawn by AutoCAD software.
- The possibility of characterization of the ideas adopted for the physical in order to distinguish to some parts of the human form of discrimination, such as palm or face shape.
- The possibility of applying the idea of the discovery of angles within geometric shapes for measurement based on the mathematical relationships.

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APPENDIX (A)

Table (2) The four properties of geometric shapes with varying dimensions of the image

shape	Size imag	Contrast	Correlation	Energy	Homogeneity
Crile	50,50	0.0718	0.2165	0.8416	0.9641
	100,100	0.0368	0.2589	0.915	0.9816
	150,150	0.0258	0.2559	0.9403	0.9871
	200.200	0.0192	0.2471	0.9557	0.9904
	250,250	0.0156	0.2577	0.9637	0.9922
	300,300	0.0129	0.2703	0.9695	0.9935
Rectangle	50,50	0.0637	0.4628	0.8219	0.9682
	100,100	0.0372	0.471	0.8939	0.9814
	150,150	0.0251	0.4845	0.927	0.9875
	200.200	0.019	0.4883	0.9442	0.9905
	250,250	0.0154	0.4874	0.9547	0.9923
	300,300	0.0128	0.4922	0.9622	0.9936
Ellipse	50,50	0.0376	0.5204	0.8856	0.9812
	100,100	0.0206	0.5083	0.9379	0.989
	150,150	0.0141	0.5052	0.9575	0.9929
	200.200	0.0122	0.4608	0.9654	0.9939
	250,250	0.0102	0.4447	0.9715	0.9949
	300,300	0.0085	0.4498	0.9762	0.9958
Polygon	50,50	0.0657	0.3389	0.8392	0.9671
	100,100	0.0337	0.3525	0.9153	0.9831
	150,150	0.025	0.3459	0.9375	0.9875
	200.200	0.0182	0.3339	0.9548	0.9909
	250,250	0.0151	0.3383	0.9624	0.9925
	300,300	0.0126	0.3142	0.9691	0.9937
Triangle	50,50	0.0669	0.2871	0.8436	0.9665
	100,100	0.0356	0.3176	0.9136	0.9822
	150,150	0.0251	0.3174	0.9389	0.9875
	200.200	0.0188	0.3262	0.9537	0.9906
	250,250	0.0153	0.3228	0.9624	0.9924
	300,300	0.0128	0.3261	0.9683	0.9936
Irregular	50,50	0.0732	0.2614	0.8331	0.9634
	100,100	0.0352	0.2747	0.9176	0.9824
	150,150	0.0238	0.2591	0.9446	0.9881
	200.200	0.0178	0.2846	0.9555	0.9907
	250,250	0.0156	0.2878	0.9627	0.9922
	300,300	0.0127	0.3081	0.969	0.9936

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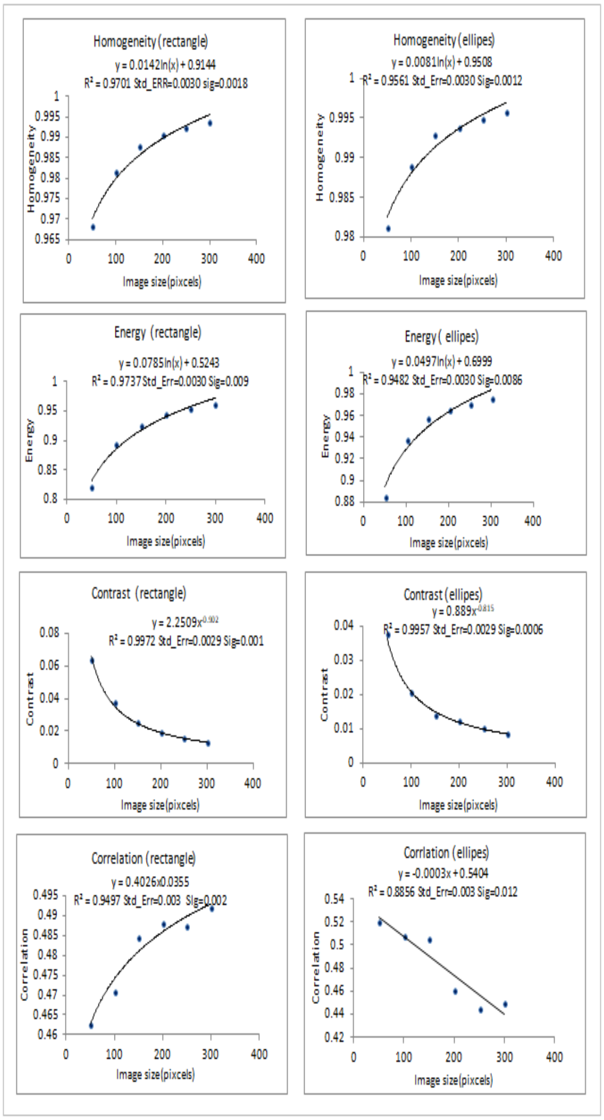
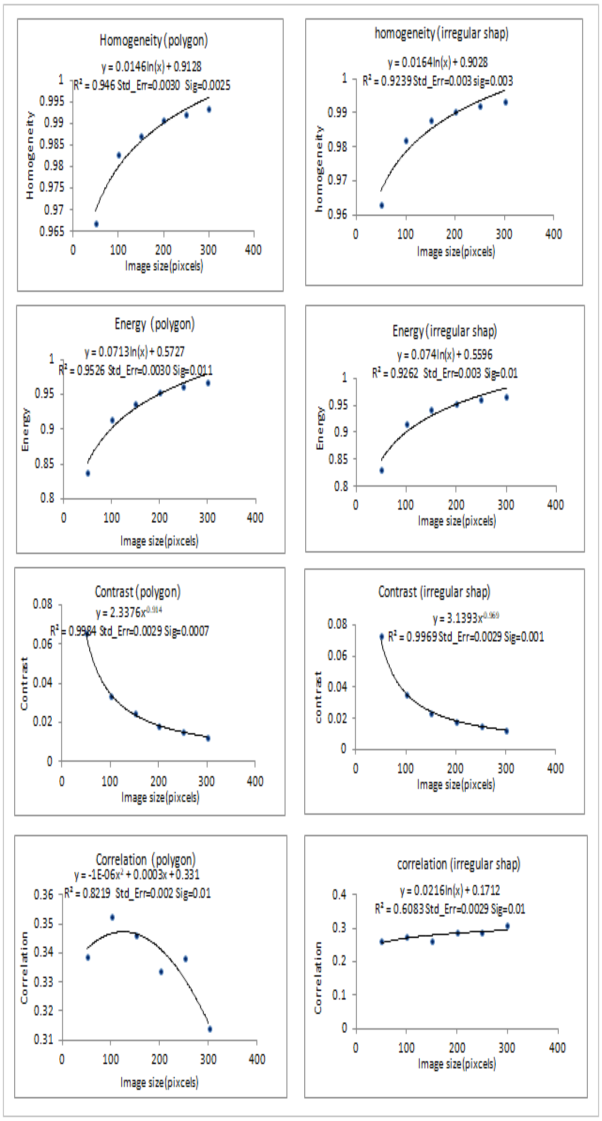
Table (3) Measured values of the coefficient of determination, Standard Err and the calculated significant level of the geometric shapes.

Feature	shape	Coff. deter.	Std_Err	Sig.
Homogeneity	Circle	0.94	0.0028	0.003
	Rectangle	0.97	0.003	0.001
	Ellipse	0.95	0.003	0.001
	Polygon	0.94	0.003	0.002
	Triangle	0.95	0.003	0.002
	Irregular	0.92	0.003	0.003
Contrast	Circle	0.99	0.0029	0.003
	Rectangle	0.99	0.002	0.001
	Ellipse	0.99	0.002	0.006
	Polygon	0.99	0.002	0.007
	Triangle	0.99	0.002	0.003
	Irregular	0.99	0.002	0.01
Energy	Circle	0.95	0.003	0.01
	Rectangle	0.97	0.003	0.009
	Ellipse	0.94	0.003	0.008
	Polygon	0.95	0.003	0.01
	Triangle	0.95	0.003	0.01
	Irregular	0.92	0.003	0.01
Correlation	Circle	0.67	0.0029	0.01
	Rectangle	0.94	0.003	0.002
	Ellipse	0.88	0.003	0.01
	Polygon	0.82	0.002	0.01
	Triangle	0.82	0.002	0.006
	Irregular	0.60	0.002	0.01

APPENDIX (B)





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